Applied Macroeconomics

Practical Session L6

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The investigation of the dynamic interactions of investment, income, and consumption in the United States involves analyzing the relationship between these three economic variables over time.

By studying the patterns and relationships between these three variables over time, we can gain insight into the dynamics of the US economy and the factors that drive economic growth and stability.

We will follow the following structure to obtain the best possible model:

1. ADF test
2. Determine the optimal lag length for the VAR model.
3. Estimate the reduced-form VAR model.
4. See the impulse response functions.
5. Estimate an exactly identified structural VAR (SVAR) model.

Overall, the investigation of the dynamic interactions of investment, income, and consumption in the United States is an important area of research that can provide valuable insights into the workings of the US economy and inform economic policy and investment decisions.

1. Perform the ADF test to confirm that the three variables are stationary.

```
. dfuller dlrinv, lags(12)

Augmented Dickey-Fuller test for unit root         Number of obs   =       174

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -5.056            -3.485            -2.885            -2.575
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. dfuller dlrgdp, lags(12)

Augmented Dickey-Fuller test for unit root         Number of obs   =       174

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -4.389            -3.485            -2.885            -2.575
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0003

. dfuller dlrcons, lags(12)

Augmented Dickey-Fuller test for unit root         Number of obs   =       174

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -3.876            -3.485            -2.885            -2.575
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0022
```

The results of the Augmented Dickey Fuller test suggest that all three variables, investment, income, and consumption, are stationary. This means that the mean, variance, and autocorrelation structure of these variables remain relatively constant over time, indicating a greater degree of stability and predictability with and without the trend (not shown).

2. Using the *varsoc* command and diagnostic checks on the residuals, determine the optimal lag length for the VAR model.

```
. varsoc dlrinv dlrgdp dlrcons, maxlag(12)

   Selection-order criteria
   Sample:  1962q2 - 2005q4                     Number of obs      =       175
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-645.462				.331995	7.411	7.433	7.46525
1	-610.406	70.112	9	0.000	.246499	7.11321	7.20124*	7.33023*
2	-601.62	17.573	9	0.040	.247127	7.11565	7.2697	7.49543
3	-593.73	15.779	9	0.072	.250345	7.12834	7.34841	7.67087
4	-587.617	12.225	9	0.201	.25886	7.16134	7.44743	7.86664
5	-576.117	23	9	0.006	.251749	7.13277	7.48488	8.00083
6	-563.182	25.871*	9	0.002	.240927*	7.08779*	7.50592	8.11861
7	-559.091	8.1815	9	0.516	.255197	7.1439	7.62805	8.33747
8	-550.805	16.572	9	0.056	.257774	7.15206	7.70223	8.50839
9	-544.611	12.388	9	0.192	.266818	7.18412	7.80031	8.70322
10	-538.464	12.294	9	0.197	.276492	7.21673	7.89894	8.89858
11	-534.379	8.1683	9	0.517	.293548	7.27291	8.02114	9.11753
12	-529.301	10.157	9	0.338	.308362	7.31772	8.13197	9.3251

```
   Endogenous:  dlrinv dlrgdp dlrcons
    Exogenous:  _cons
```

Using 12 lags we found that the AIC suggested that the optimal lag length is 6, while the HQIC and SBIC indicated that the optimal lag length is 1. Now we will compare these two VAR models and determine which one is preferred analyzing the serial correlation.

Testing for autocorrelation on 6 lags

```
var dlrinv dlrgdp dlrcons, lags(1/6)

predict r_dlrinv, r eq(dlrinv)
predict r_dlrgdp, r eq(dlrgdp)
predict r_dlrcons, r eq(dlrcons)

corrgram r_dlrinv, lags(20)
corrgram r_dlrgdp, lags(20)
corrgram r_dlrcons, lags(20)
```

Output omitted for simplicity.

After running all the *corrgram* commands, we found no evidence for autocorrelation. There were no p-values lower than 0.05 in the $Prob > Q$ column.

Testing for autocorrelation on 1 lag

```
drop r_dlrinv r_dlrcons r_dlrgdp
var dlrinv dlrgdp dlrcons, lags(1)

predict r_dlrinv, r eq(dlrinv)
predict r_dlrgdp, r eq(dlrgdp)
predict r_dlrcons, r eq(dlrcons)

corrgram r_dlrinv, lags(20)
corrgram r_dlrgdp, lags(20)
corrgram r_dlrcons, lags(20)
```

We found evidence for autocorrelation on investment on lags 8 through 20.

We keep the model without autocorrelation (6 lags).

3. Estimate the reduced form var model using the number of lags chosen and run all the possible Granger causality tests.

```
. var dlrinv dlrgdp dlrcons, lags(1/6)

Vector autoregression

Sample:  1960q4 - 2005q4                        Number of obs     =        181
Log likelihood =  -595.1042                     AIC               =   7.205571
FPE            =   .2709742                     HQIC              =   7.613936
Det(Sigma_ml)  =   .1440068                     SBIC              =   8.212832

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlrinv               19     1.6595   0.3240   86.7694   0.0000
dlrgdp               19     .74305   0.3175   84.21454  0.0000
dlrcons              19    .659355   0.1531   32.72376  0.0180
----------------------------------------------------------------
```

All variables are jointly significant but just some lags are (omitted output for simplicity).

And running the Granger causality tests:

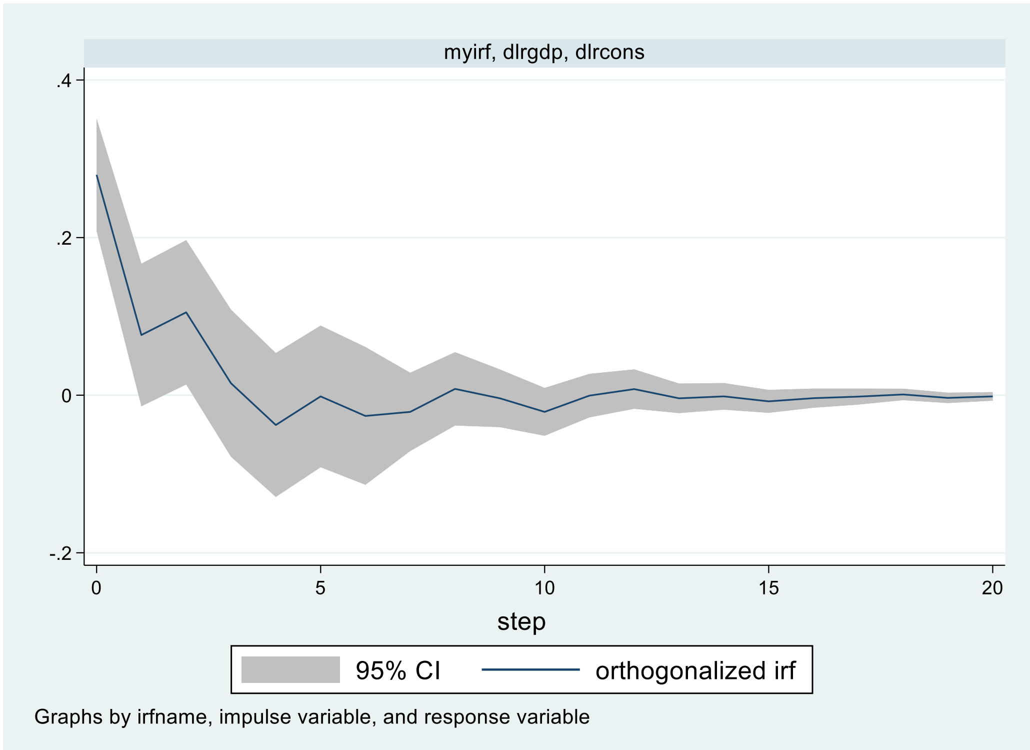
```
. vargranger

   Granger causality Wald tests

  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |            dlrinv             dlrgdp |  16.453     6    0.012    |
  |            dlrinv            dlrcons |  8.3024     6    0.217    |
  |            dlrinv                ALL |  30.926    12    0.002    |
  |--------------------------------------+---------------------------|
  |            dlrgdp             dlrinv |  24.634     6    0.000    |
  |            dlrgdp            dlrcons |  16.228     6    0.013    |
  |            dlrgdp                ALL |  51.837    12    0.000    |
  |--------------------------------------+---------------------------|
  |           dlrcons             dlrinv |  8.3244     6    0.215    |
  |           dlrcons             dlrgdp |  8.1708     6    0.226    |
  |           dlrcons                ALL |  14.685    12    0.259    |
  +------------------------------------------------------------------+
```

This table shows the results of the Granger causality Wald tests. The granger causality test evalueates whether the past values of one variable can be used to predict another variable, providing evidence of ‘causal’ relationship.

Looking at the table we can see that income (*dlrgdp*) granger causes investment (*dlrinv*) and both investment and consumption jointly granger cause income. Also, investment and investment & consumption jointly granger cause income. No variable granger causes consumption.

4. Suppose we are interested to see:
    a. How the growth rate of consumption responds to a one-time positive shock in the growth rate of income.

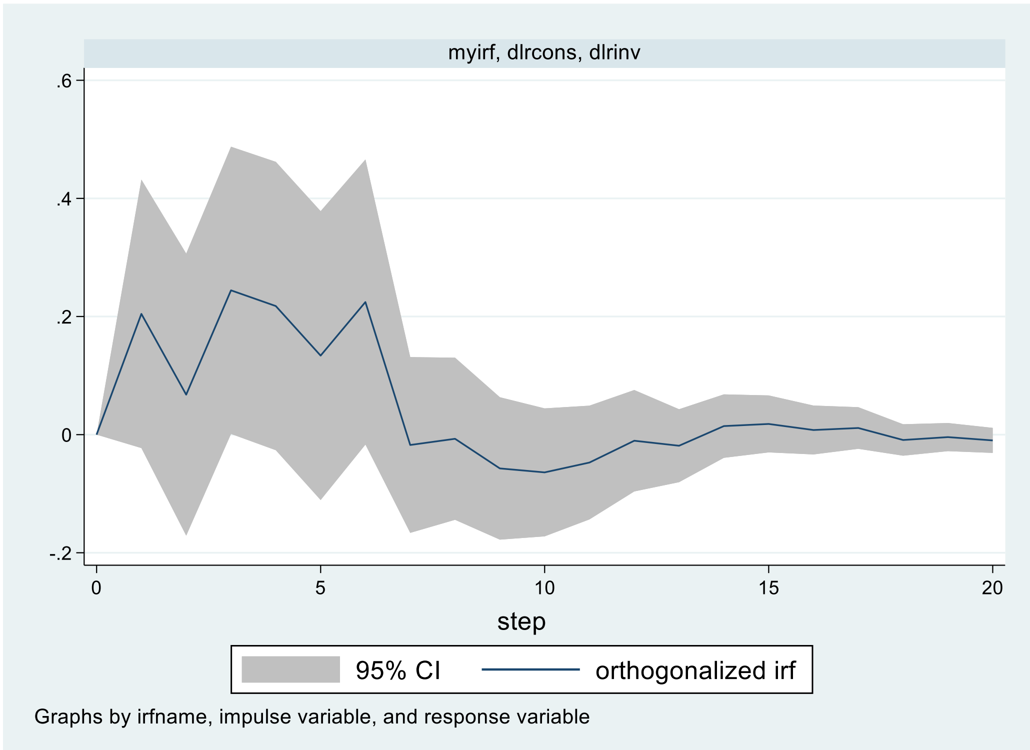
```
irf create myirf, step(20) set(myirfs, replace)

irf graph oirf, impulse(dlrgdp) response(dlrcons)
```



This graph shows that a one-standard-deviation shock to income has a positive and significant effect on consumption in the short term (step 0), with the response peaking at step 2. However, the effect diminishes over time and become statistically insignificant beyond step 3.

b. How the growth rate of investment responds to one-time positive shock in the growth rate of consumption.

```
irf graph oirf, impulse(dlrcons) response(dlrinv)
```



No step is statistically significant, meaning that a shock in consumption has no effect on investment. There could be several reasons why a shock in consumption doesn't increase investment, one possible explanation is that the increase in consumption is only temporary, and businesses are hesitant to invest in long-term projects based on short-term changes in demand.

5. Estimate an exactly-identifies structural VAR (SVAR). Assume that : (i) percentage changes in investments are not contemporaneously affected by consumption or income; (ii) percentage changes in income is affected by contemporaneous changes in investments but not consumption; (iii) percentages changes in consumption are affected by contemporaneous changes in both investments and income.

Following these assumptions we can create two matrices to apply this to the model:

```
* '\' represents a row change *
matrix A = (1,0,0 \ .,1,0 \ .,.,1)
matrix B = (.,0,0 \ 0,.,0 \ 0,0,.)
```

Now we can run the next model:

```
svar dlrinv dlrgdp dlrcons, aeq(A) beq(B) lags(1/6)
```

```
Sample:  1960q4 - 2005q4                        Number of obs     =        181
Exactly identified model                        Log likelihood    =  -595.1042

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
/A           |
         1_1 |          1  (constrained)
         2_1 |  -.2868243   .0255565   -11.22   0.000    -.3369142   -.2367345
         3_1 |  -.0629795   .0276076    -2.28   0.023    -.1170893   -.0088696
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
         3_2 |  -.5181778   .0616576    -8.40   0.000    -.6390246   -.3973311
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |          1  (constrained)
-------------+----------------------------------------------------------------
/B           |
         1_1 |   1.569981   .0825164    19.03   0.000     1.408252     1.73171
         2_1 |          0  (constrained)
         3_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   .5398032   .0283714    19.03   0.000     .4841962    .5954101
         3_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |   .4477768   .0235346    19.03   0.000     .4016498    .4939038
------------------------------------------------------------------------------
```

Here we can see every coefficient is significant and to see the estimated matrices we use:

```
matlist e(A)
matlist e(B)
```

```
. matlist e(A)

             |    dlrinv     dlrgdp    dlrcons
-------------+---------------------------------
      dlrinv |         1          0          0
      dlrgdp | -.2868243          1          0
     dlrcons | -.0629795  -.5181778          1

. matlist e(B)

             |    dlrinv     dlrgdp    dlrcons
-------------+---------------------------------
      dlrinv |  1.569981
      dlrgdp |         0   .5398032
     dlrcons |         0          0   .4477768
```

We were asked to prove that the next relationship is true:

$$dlrcons = 0.06\, dlrinv + 0.52\, dlrgdp$$

We can see at the last row of the first table that this relationship is, in fact, true.

In conclusion, the VAR and SVAR models are powerful tools for analyzing the relationship between investment, income, and consumption in the US economy. The findings suggest that income is the main driver of consumption.